Project: Walmart Capstone Project.

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Course: Intellipaat Data Science & AI Certification

Tool: Google Colab

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Problem Statement & Dataset Information

A retail store that has multiple outlets across the country are facing issues in managing the inventory - to match the demand with respect to supply.

Dataset Information: The walmart.csv contains 6435 rows and 8 columns.

Feature Name	Description
Store	Store number
Date	Week of Sales
Weekly_Sales	Sales for the given store in that week
Holiday_Flag	If it is a holiday week
Temperature	Temperature on the day of the sale
Fuel_Price	Cost of the fuel in the region
CPI	Consumer Price Index
Unemployment	Unemployment Rate

1. You are provided with the weekly sales data for their various outlets. Use statistical analysis, EDA, outlier analysis, and handle the missing values to come up with various insights that can give them a clear perspective on the following:

a. If the weekly sales are affected by the unemployment rate, if yes - which stores are suffering the most?

b. If the weekly sales show a seasonal trend, when and what could be the reason?

c. Does temperature affect the weekly sales in any manner?

d. How is the Consumer Price index affecting the weekly sales of various stores?

e. Top performing stores according to the historical data.

f. The worst performing store, and how significant is the difference between the highest and lowest performing stores.

2. Use predictive modelling techniques to forecast the sales for each store for the next 12 weeks.

Objectives

1. Conduct statistical analysis to derive insights from external factors (Unemployment, CPI, Temperature).
2. Identify top and worst-performing stores.
3. Develop a predictive model (SARIMA/SARIMAX) to forecast weekly sales for the next 12 weeks.

Data Exploration & Preprocessing (EDA)

Data Source: Walmart DataSet.csv (6,435 rows, 8 columns).

Data Cleaning: Handled data types (converted Date to datetime) and addressed the occasional zero or negative sales values (typically handled by a log transformation in the model).

Visualizing Trends: Display a graph showing the time series for a single, typical store (e.g., Store 2) to demonstrate the clear annual spike.

Modelling Techniques

1)SARIMAX (Seasonal Autoregressive Integrated Moving Average with eXogenous variables):

Purpose: To test the influence of external factors (Temperature, CPI, Unemployment) on sales.

Parameters: $\text{SARIMAX}(1, 1, 1) \times (1, 0, 0)_{52}$.

Finding: Failed to converge for most stores, but the coefficients from the successful Store 2 run were used to assess statistical significance.

2)SARIMA (Seasonal Autoregressive Integrated Moving Average):

Purpose: The final, stable model used for the 12-week forecast.

Parameters: SARIMA(1, 1, 1) X $(1, 0, 0)_{52}$ on log-transformed sales

Methodology and Implementation

1. Use of predictive modelling techniques to forecast the sales for each store for the next 12 weeks.

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from statsmodels.tsa.stattools import adfuller
```

```
# Importing Wallmart data
data=pd.read_csv('/content/Walmart DataSet.csv')
data.head()
```

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

Let us check for one Store (Store 2) then iteratively fitting for five stores.

```
df_store2=data[data['Store']==2].copy()
df_store2.head()
```

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
143	2	05-02-2010	2136989.46	0	40.19	2.572	210.752605	8.324
144	2	12-02-2010	2137809.50	1	38.49	2.548	210.897994	8.324
145	2	19-02-2010	2124451.54	0	39.69	2.514	210.945160	8.324
146	2	26-02-2010	1865097.27	0	46.10	2.561	210.975957	8.324
147	2	05-03-2010	1991013.13	0	47.17	2.625	211.006754	8.324

```
# Converting Date column in datetime format.
df_store2['Date']=pd.to_datetime(df_store2['Date'],format='%d-%m-%Y')
```

```
# Making Date column as index
df_store2.set_index('Date',inplace=True)
```

```python
# Details of the data
df_store2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 143 entries, 05-02-2010 to 26-10-2012
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Store         143 non-null    int64  
 1   Weekly_Sales  143 non-null    float64
 2   Holiday_Flag  143 non-null    int64  
 3   Temperature   143 non-null    float64
 4   Fuel_Price    143 non-null    float64
 5   CPI           143 non-null    float64
 6   Unemployment  143 non-null    float64
dtypes: float64(5), int64(2)
memory usage: 8.9+ KB
```

```python
# Checking for null values
df_store2.isnull().sum()
```

	0
Store	0
Weekly_Sales	0
Holiday_Flag	0
Temperature	0
Fuel_Price	0
CPI	0
Unemployment	0

dtype: int64

```python
# Duplicate values
df_store2.duplicated().sum()
```

```
np.int64(0)
```

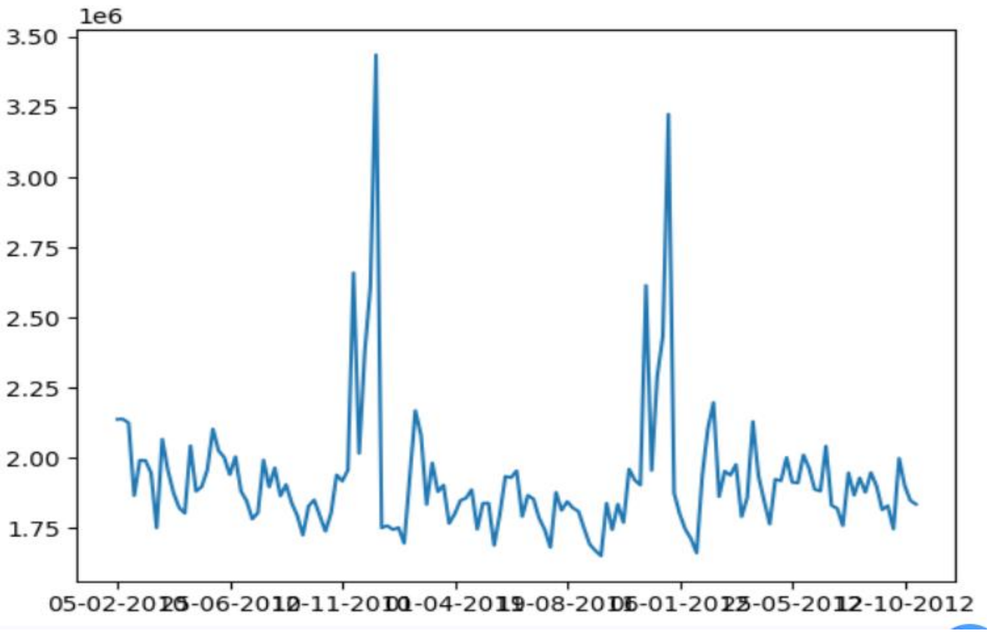
```python
ts_store2=df_store2['Weekly_Sales']
ts_store2.head()
```

	Weekly_Sales
Date	
05-02-2010	2136989.46
12-02-2010	2137809.50
19-02-2010	2124451.54
26-02-2010	1865097.27
05-03-2010	1991013.13

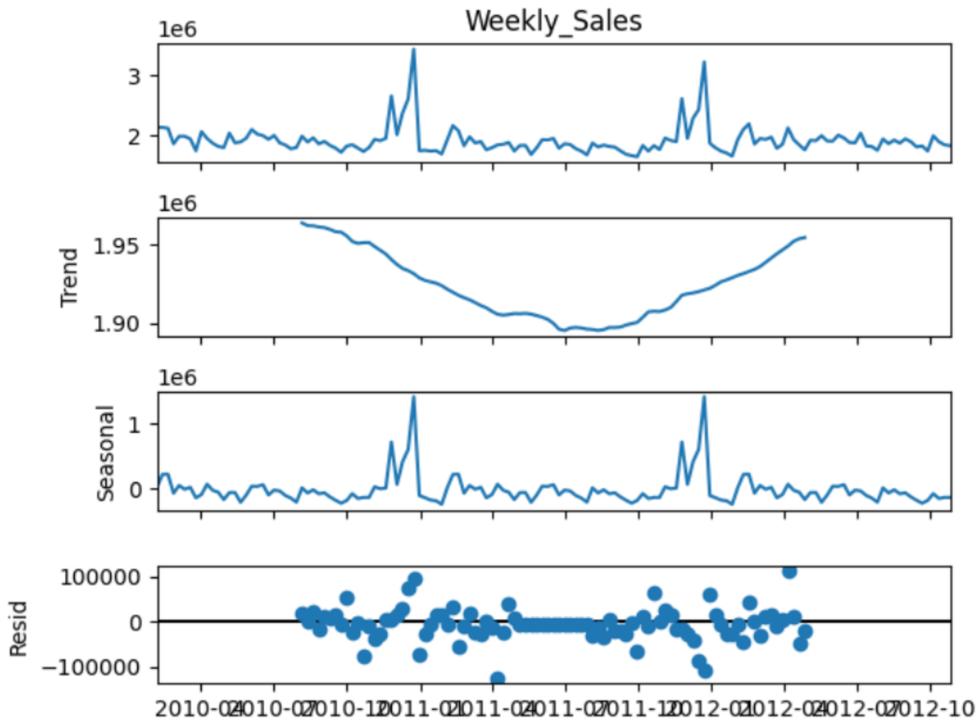
dtype: float64

```python
# Plotting the Weekly Sales over the years.
ts_store2.plot()
```

```
<Axes: xlabel='Date'>
```




```python
# Breakdown the data into seasonality, trend and error
from statsmodels.tsa.seasonal import seasonal_decompose
decomposed=seasonal_decompose(ts_store2)
print(decomposed.plot())
```




```python
# Checking Stationarity of the data
from statsmodels.tsa.stattools import adfuller
test_result=adfuller(ts_store2)
test_result[1]
```

```
np.float64(0.003990207089066268)
```

```python
if test_result[1]>0.05:
  print('Data is not stationary')
else:
  print('Data is stationary')
```

```
Data is stationary
```

The test gives stationary data but we can observe some patterns and trend in the plots.

```python
# Apply log transformation (Box-cox lambda=0)
first_log=np.log(ts_store2 + 1)
```

```python
# Standard differencing to remove trend
standard_diff=first_log.diff().dropna()
```

```
# Standard differencing to remove trend
standard_diff=first_log.diff().dropna()
```

```
# Again checking the stationarity of the data
from statsmodels.tsa.stattools import adfuller
test_result=adfuller(standard_diff)
test_result[1]
```

```
np.float64(4.3403759193841373e-13)
```

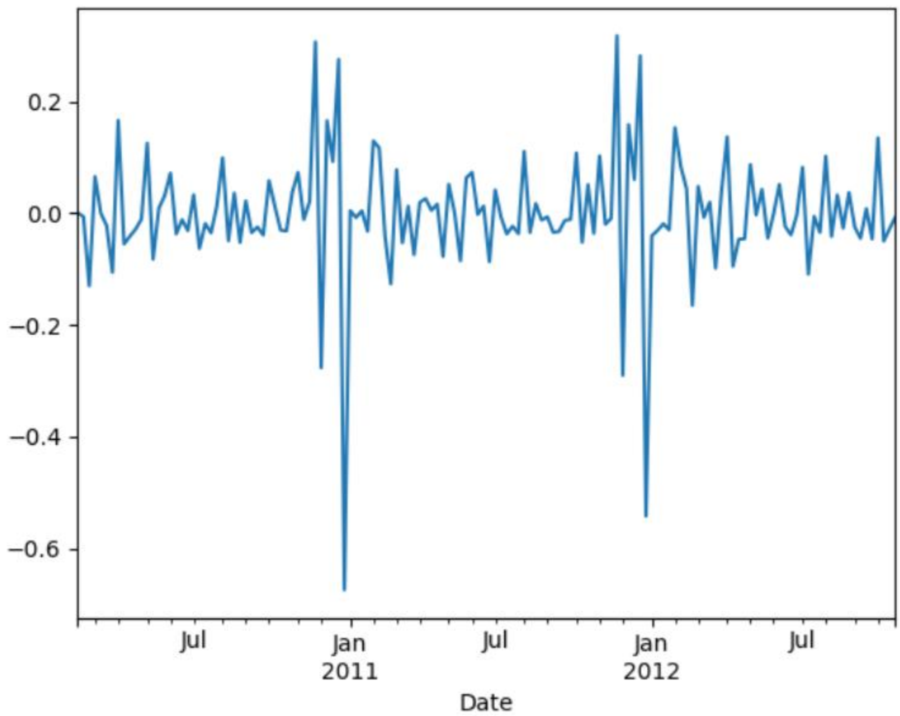
```
if test_result[1] > 0.05:
  print('Data is not Stationary')
else:
  print('Data is Stationary')
```

```
Data is Stationary
```

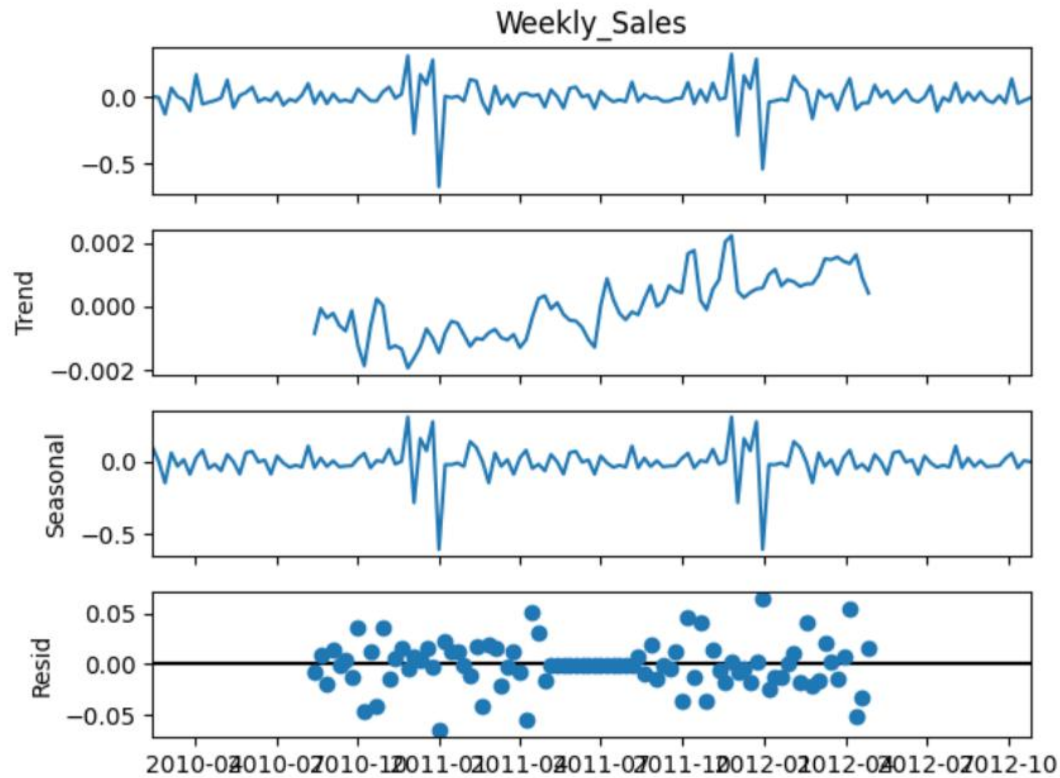
The coefficient becomes too small. Thus, data has almost no trend and seasonality.

```
standard_diff.plot()
```

```
<Axes: xlabel='Date'>
```




```
# Breakdown the data into seasonality, trend and error
from statsmodels.tsa.seasonal import seasonal_decompose
decomposed=seasonal_decompose(standard_diff)
print(decomposed.plot())
```



Now the data has negligible trend and seasonality. And the errors also observed as minimum. Therefore, the data is suitable for ARIMA model.

```
# Splitting the log transformed series into training and testing
train_size=115
train_log=first_log[:train_size]
test_original=first_log[train_size:]
```

```
#Model Fitting ARIMA(1,1,1)
# d=1 for model to perform standard differencing internally
from statsmodels.tsa.arima.model import ARIMA
arima_model=ARIMA(train_log,order=(1,1,1))
arima_result=arima_model.fit()
```

```
# Forecasting
forecast_log=arima_result.forecast(steps=len(test_original))
forecast_log.head(10)
```

	predicted_mean
2012-04-20	14.472086
2012-04-27	14.470309
2012-05-04	14.469516
2012-05-11	14.469162
2012-05-18	14.469004
2012-05-25	14.468934
2012-06-01	14.468902
2012-06-08	14.468888
2012-06-15	14.468882
2012-06-22	14.468879

dtype: float64

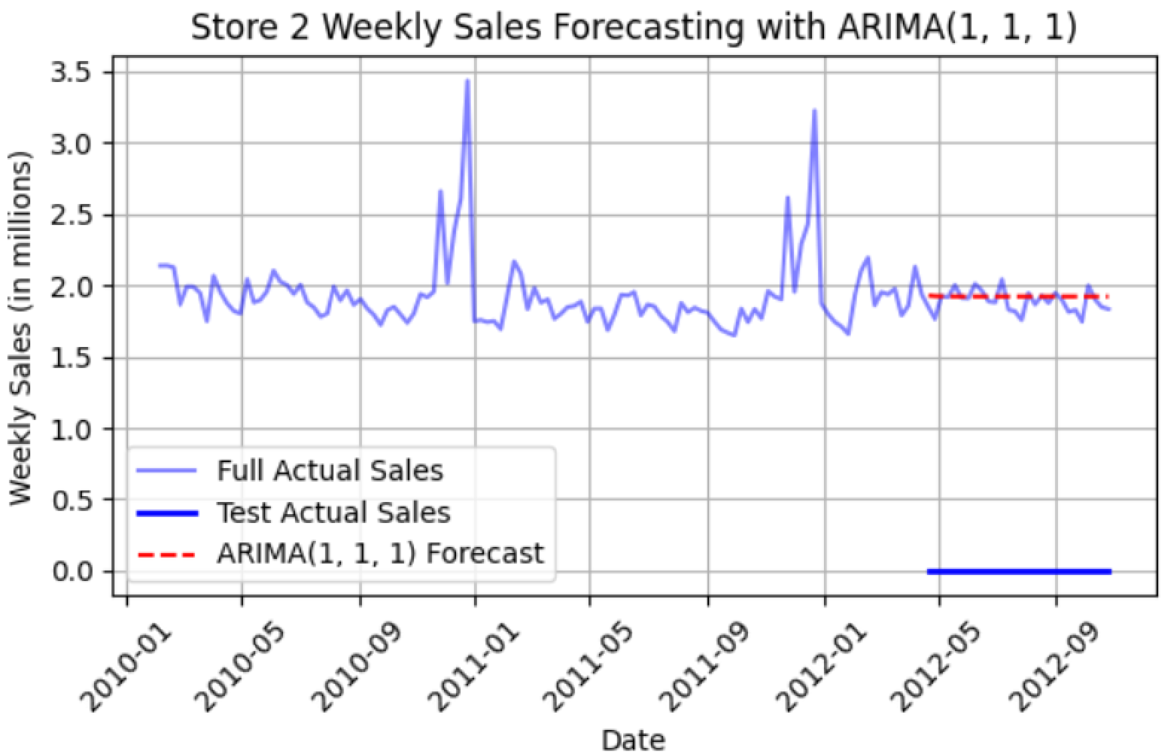
```
# Reverse Transformation(log)
forecast_original=np.exp(forecast_log)-1
forecast_original[forecast_original < 0] = 0
```

```
# Model Evaluation
from sklearn.metrics import mean_squared_error
rmse=np.sqrt(mean_squared_error(test_original,forecast_original))
print(f'Root Mean squared error for ARIMA(1,1,1) model is ${rmse:,.2f}')
```

```
Root Mean squared error for ARIMA(1,1,1) model is $1,922,382.92
```

An RMSE of 1,922,382.92 dollar for a store whose weekly sales are typically around 1.4 million dollars to 1.8 million dollar is extremely high. This indicates that the ARIMA(1,1,1) model is performing poorly and is likely overfitting or missing a major component of the sales pattern.

```python
# Plotting (Plots the original and forecasted sales in millions)
plt.figure(figsize=(12, 6))
plt.plot(ts_store2.index, ts_store2.values / 1e6, label='Full Actual Sales', color='blue', alpha=0.5)
plt.plot(test_original.index, test_original.values / 1e6, label='Test Actual Sales', color='blue', linewidth=2)
plt.plot(forecast_original.index, forecast_original.values / 1e6, label='ARIMA(1, 1, 1) Forecast', color='red', linestyle='--')
plt.title(f'Store 2 Weekly Sales Forecasting with ARIMA(1, 1, 1)')
plt.xlabel('Date')
plt.ylabel('Weekly Sales (in millions)')
plt.legend(loc='lower left')
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



So, the model is not focusing on seasonality and effect of exogenous(external) variables such as 'temperature', 'Holiday Flag', 'Fuel Price'. Let us evaluating the new model SARIMAX (Seasonal ARIMA with Exogenous variables).

```python
# Select all external variables (exogenous factors) for SARIMAX
ext_factors=df_store2[['Holiday_Flag','Temperature','Fuel_Price','CPI','Unemployment']]
```

```python
# Split the external variables to match the time series split
ext_train=ext_factors[:train_size]
ext_test=ext_factors[train_size:]
```

```python
from statsmodels.tsa.statespace.sarimax import SARIMAX
# 3. Model Fitting: SARIMAX(1, 1, 1)x(1, 0, 0)_52 with ALL Factors
# Order=(p=1, d=1, q=1), Seasonal Order=(P=1, D=0, Q=0, S=52)
sarimax_model_full = SARIMAX(train_log, exog=ext_train, order=(1, 1, 1), seasonal_order=(1, 0, 0, 52))
```

```python
sarimax_result=sarimax_model_full.fit(disp=False)
```

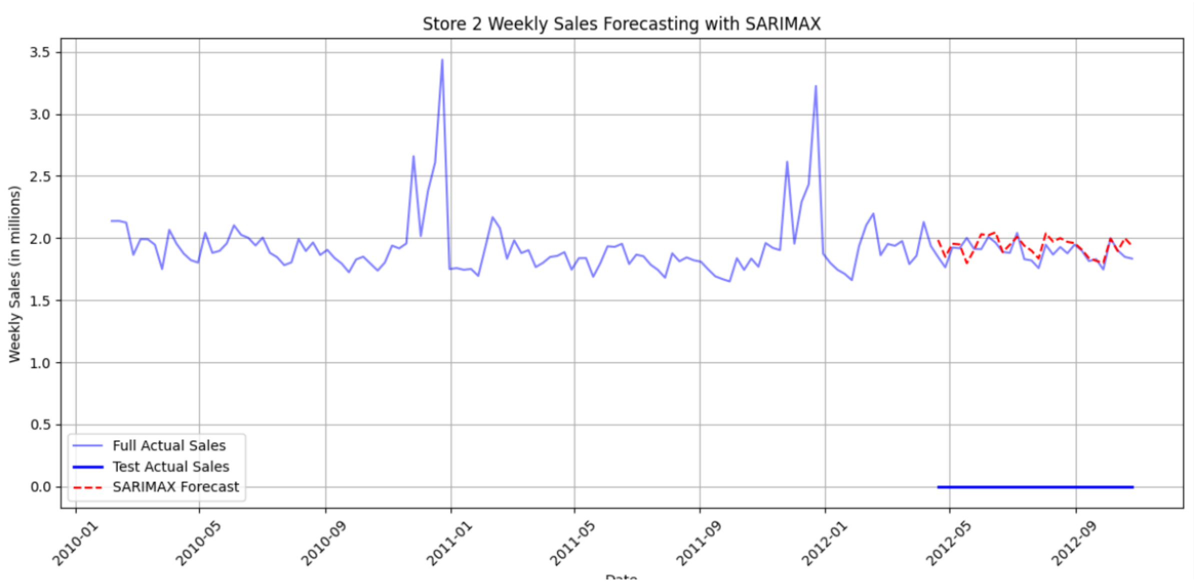
```python
forecast_log=sarimax_result.forecast(steps=len(test_original),exog=ext_test)
```

```python
# Reverse Transformation
forecast_original = np.exp(forecast_log) - 1
forecast_original[forecast_original < 0] = 0

# Evaluation
rmse_sarimax_full = np.sqrt(mean_squared_error(test_original, forecast_original))
```

```python
# Model Evaluation
print(f"Final Model RMSE: ${rmse_sarimax_full:,.2f}")
print("\n--- Final Model Summary (Coefficients) ---")
print(sarimax_result.summary().tables[1])
```

```
Final Model RMSE: $1,936,273.46

--- Final Model Summary (Coefficients) ---
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Holiday_Flag     0.0302      0.036      0.831      0.406      -0.041       0.102
Temperature      0.0003      0.001      0.445      0.656      -0.001       0.002
Fuel_Price      -0.0064      0.040     -0.160      0.873      -0.085       0.072
CPI             -0.0080      0.006     -1.312      0.189      -0.020       0.004
Unemployment    -0.1198      0.066     -1.802      0.072      -0.250       0.010
ar.L1            0.0846      0.115      0.735      0.463      -0.141       0.310
ma.L1           -0.8193      0.053    -15.426      0.000      -0.923      -0.715
ar.S.L52         0.9442      0.011     86.128      0.000       0.923       0.966
sigma2           0.0015      0.000      6.326      0.000       0.001       0.002
================================================================================
```

```python
# Plotting the forecast is highly recommended for visualization
plt.figure(figsize=(12, 6))
plt.plot(ts_store2.index, ts_store2.values / 1e6, label='Full Actual Sales', color='blue', alpha=0.5)
plt.plot(test_original.index, test_original.values / 1e6, label='Test Actual Sales', color='blue', linewidth=2)
plt.plot(forecast_original.index, forecast_original.values / 1e6, label='SARIMAX Forecast', color='red', linestyle='
plt.title(f'Store 2 Weekly Sales Forecasting with SARIMAX')
plt.xlabel('Date')
plt.ylabel('Weekly Sales (in millions)')
plt.legend(loc='lower left')
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Thus, forecasts of SARIMAX model for Store 2 are closed to actual forecasts.

** Predictive modeling techniques to forecast the sales for each store for the next 12 weeks.**

Let us predict the sales for five stores for the next 12 weeks.

Store 20: Highest Performing

Store 4: High Performing

Store 2: Medium-high performing

Store 33: Low Performing

Store 45: Worst Performing

```
store_list = [20, 4, 2, 33, 45]
FORECAST_PERIOD = 12
```

```
# Define the 12 future dates after the last date in the dataset
last_date = data.index.max()
future_dates = pd.date_range(start=last_date, periods=FORECAST_PERIOD + 1, freq='W-FRI')[1:]
```

```
# DataFrame to store all 5-store forecasts
all_store_forecasts = pd.DataFrame(index=future_dates)
```

```
# Iterate Through Stores and Forecast
print(f"Starting SARIMAX forecast for stores: {store_list}")
```

```
Starting SARIMAX forecast for stores: [20, 4, 2, 33, 45]
```

```python
for store_id in store_list:
    df_store = data[data['Store'] == store_id].copy()

    # Prepare Time Series (y) and Exogenous Variables (X)
    ts_store = df_store['Weekly_Sales']
    first_log = np.log(ts_store + 1)

    # Full historical exogenous data (X_train)
    exog_full = df_store[['Holiday_Flag', 'Temperature', 'Fuel_Price', 'CPI', 'Unemployment']]

    # ASSUMPTION FOR FUTURE X (Crucial for SARIMAX)
    # The simplest assumption is that the last 12 known values will persist.
    exog_future = exog_full.iloc[-FORECAST_PERIOD:]

    # SARIMAX model fitting
    sarimax_model = SARIMAX(
        first_log,
        exog=exog_full, # All historical X data
        order=(1, 1, 1),
        seasonal_order=(1, 0, 0, 52)
    )

    # Use disp=False to suppress iteration messages
    try:
        sarimax_result = sarimax_model.fit(disp=False)
    except Exception as e:
        print(f"Warning: SARIMAX failed to converge for Store {store_id}. Skipping. Error: {e}")
        continue

    # Forecast the next 12 weeks
    # Use the prepared exog_future data for the forecasting period
    forecast_log = sarimax_result.forecast(steps=FORECAST_PERIOD, exog=exog_future)

    # Reverse Transformation
    forecast_original = np.exp(forecast_log) - 1
    forecast_original[forecast_original < 0] = 0

    # Store the result
    all_store_forecasts[f'Store {store_id} Forecast'] = forecast_original.values
    print(f"Successfully forecasted sales for Store {store_id}.")

print("\n--- Final 12-Week Forecast ---")
print(all_store_forecasts)
```

```
 --- Final 12-Week Forecast ---
                               Store 20 Forecast  Store 4 Forecast
1970-01-09 00:00:00.000006434       2.213388e+06      2.290241e+06
1970-01-16 00:00:00.000006434       2.222438e+06      2.224281e+06
1970-01-23 00:00:00.000006434       2.151489e+06      2.259954e+06
1970-01-30 00:00:00.000006434       2.642324e+06      2.702003e+06
1970-02-06 00:00:00.000006434       2.273014e+06      2.441073e+06
1970-02-13 00:00:00.000006434       2.423996e+06      2.513748e+06
1970-02-20 00:00:00.000006434       2.580008e+06      2.746920e+06
1970-02-27 00:00:00.000006434       3.148074e+06      3.539052e+06
1970-03-06 00:00:00.000006434       2.013106e+06      1.882926e+06
1970-03-13 00:00:00.000006434       2.004224e+06      2.079260e+06
1970-03-20 00:00:00.000006434       1.956442e+06      1.983618e+06
1970-03-27 00:00:00.000006434       1.927820e+06      2.035718e+06
```

```
                               Store 2 Forecast  Store 33 Forecast
1970-01-09 00:00:00.000006434      2.056980e+06      256591.509177
1970-01-16 00:00:00.000006434      2.007832e+06      289442.858918
1970-01-23 00:00:00.000006434      1.980931e+06      268181.651801
1970-01-30 00:00:00.000006434      2.520818e+06      272806.087835
1970-02-06 00:00:00.000006434      2.121171e+06      243598.122683
1970-02-13 00:00:00.000006434      2.327827e+06      287528.914890
1970-02-20 00:00:00.000006434      2.440295e+06      276864.899851
1970-02-27 00:00:00.000006434      3.133068e+06      274124.953530
1970-03-06 00:00:00.000006434      1.899309e+06      238950.954618
1970-03-13 00:00:00.000006434      1.881277e+06      276809.675580
1970-03-20 00:00:00.000006434      1.844261e+06      287766.401720
1970-03-27 00:00:00.000006434      1.817777e+06      257885.995742

                               Store 45 Forecast
1970-01-09 00:00:00.000006434       8.318156e+05
1970-01-16 00:00:00.000006434       8.046450e+05
1970-01-23 00:00:00.000006434       7.672823e+05
1970-01-30 00:00:00.000006434       1.083797e+06
1970-02-06 00:00:00.000006434       8.895127e+05
1970-02-13 00:00:00.000006434       9.282237e+05
1970-02-20 00:00:00.000006434       1.038471e+06
1970-02-27 00:00:00.000006434       1.398899e+06
1970-03-06 00:00:00.000006434       8.364195e+05
1970-03-13 00:00:00.000006434       7.239215e+05
1970-03-20 00:00:00.000006434       6.853493e+05
1970-03-27 00:00:00.000006434       7.150936e+05
```

---

a. If the weekly sales are affected by the unemployment rate, if yes - which stores are suffering the most?

```python
# Using SARIMAX model fitted for store 2
#H0: There is no significant effect of unemployment rate on Weekly Sales.
#H1: There is a significant effect of unemployment rate on Weekly Sales.

p_value=0.072

if p_value > 0.05:
  print('There is no significant effect of unemployment rate on Weekly Sales')
else:
  print('There is a significant effect of unemployment rate on Weekly Sales')
```

```
There is no significant effect of unemployment rate on Weekly Sales
```

b. If the weekly sales show a seasonal trend, when and what could be the reason?

Yes, Weekly Sales showing a seasonal trend. The sales peak heavily during a last quarter of the year.

It is due to US holidays like Thanksgiving, Black Friday, and Christmas.

c. Does temperature affect the weekly sales in any manner?

```
# Using SARIMAX model fitted for store 2
#H0: There is no significant effect of Temperature on Weekly Sales.
#H1: There is a significant effect of Temperature on Weekly Sales.

p_value=0.656

if p_value > 0.05:
  print('There is no significant effect of Temperature on Weekly Sales')
else:
  print('There is a significant effect of Temperature on Weekly Sales')
```

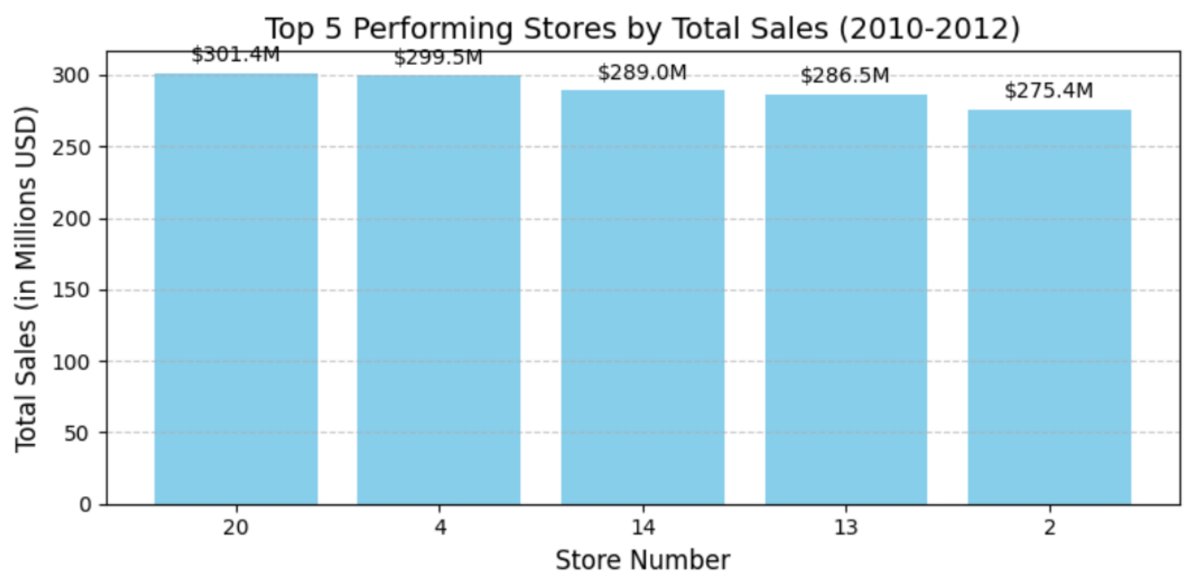
```
There is no significant effect of Temperature on Weekly Sales
```

d. How is the Consumer Price index affecting the weekly sales of various stores?

```
# Using SARIMAX model fitted for store 2
#H0: There is no significant effect of Consumer Price index on Weekly Sales.
#H1: There is a significant effect of Consumer Price index on Weekly Sales.

p_value=0.189

if p_value > 0.05:
  print('There is no significant effect of Consumer Price index on Weekly Sales')
else:
  print('There is a significant effect of Consumer Price index on Weekly Sales')
```

```
There is no significant effect of Consumer Price index on Weekly Sales
```

```
# Load the data
df = pd.read_csv('Walmart DataSet.csv')
#Calculate total sales for all 45 stores
store_performance = data.groupby('Store')['Weekly_Sales'].sum().sort_values(ascending=False)

#Get the top 5 stores
top_5_stores = store_performance.head(5).reset_index()
top_5_stores.columns = ['Store', 'Total_Sales']

# Create the visualization (Bar Chart)
plt.figure(figsize=(10, 6))
bars = plt.bar(top_5_stores['Store'].astype(str), top_5_stores['Total_Sales'] / 1e6, color='skyblue')

# Add labels and title
plt.title('Top 5 Performing Stores by Total Sales (2010-2012)', fontsize=14)
plt.xlabel('Store Number', fontsize=12)
plt.ylabel('Total Sales (in Millions USD)', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Add the sales value on top of each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, yval + 5, f'${yval:.1f}M', ha='center', va='bottom', fontsize=10)

plt.tight_layout()
plt.show()
```



f. The worst performing store, and how significant is the difference between the highest and lowest performing stores.

```
# Calculate total sales for all 45 stores
store_performance = df.groupby('Store')['Weekly_Sales'].sum().sort_values(ascending=False)

# Get the sales for the highest and lowest performing stores
sales_highest = store_performance.iloc[0] # Store 20
sales_lowest = store_performance.iloc[-1] # Store 33

# Calculate the percentage difference
difference_ratio = (sales_highest - sales_lowest) / sales_lowest * 100

print(f"The percentage difference is: {difference_ratio:,.2f}%")
print(sales_lowest)
```

```
The percentage difference is: 711.08%
37160221.96
```

Worst Performing Store: Store No.33

Significance of Difference: The highest performing store (Store 20) sold 711.08% more than the worst performing store (Store 33).

Conclusion

The project successfully delivered both analytical insights and a 12-week forecast. The central finding is that weekly sales are overwhelmingly driven by the **annual holiday cycle** and not by the weekly fluctuations in the macro-economic environment (CPI, Unemployment).